DIVERSE OCCUPANCY SIMULATION AND PRESENCE SENSING VIABILITY FOR RESIDENTIAL THERMAL ENERGY REGULATION: REVIEW AND INITIAL FINDINGS

Tarek Sherif and Tarek Rakha
School of Architecture, Georgia Institute of Technology, Atlanta, GA, USA

ABSTRACT

The rapid progression of human sensing technology development for energy regulation in indoor spaces provides a new medium of insight for the previously difficult to replicate complexity of human behavior in Building Performance Simulation (BPS). This paper's aims are twofold: 1) investigate the evolution and current state of BPS occupancy schedules and their connection with the errors, limitations and deviations of sensing technologies. And 2) evaluate the current viability of using low cost sensing technologies in thermal (heating and cooling) energy regulation. A simulation-based workflow measured the impact of human presence's false sensing and provided a maximum acceptable frequency of false sensing. The goal was to identify the highest number of false positive sensing that would still outperform a targeted 30% energy loss benchmark, in order to evaluate the feasibility of deploying such sensing technologies across United States residential buildings.

INTRODUCTION

Significant advancements were made in the field of BPS in the past decades in terms of representing geometrical attributes and physical phenomenon of the built environment. Other contextual factors, like accurate climate modeling, are now investigated with increasing accuracy and precision. Occupancy pattern simulation representing the influence of building inhabitants on energy use, on the other hand are comparably less developed (Mahdavi and Tahmasebi 2019). The impact of occupants on energy use in buildings has been recognized as far back as 1978 by Sonderegger, who stipulated that occupant behavior may influence a 71% variation in building energy demands (C.Sonderegger 1978). The influence of those inhabitants is expected to grow in the future, with a predicted decrease in misused energy attributed to building characteristics as a result of enhanced regulation guidelines and improved building thermal properties (Guerra Santin, Itard, and Visscher 2009). Capturing the impact of individuals on energy consumption in buildings can, therefore, increase the accuracy of future simulations and reduce the disparity between simulated and actual energy use (Mahdavi and Tahmasebi 2019). Occupancy schedules have and will undoubtedly play a key role in regulating energy consumption by tightly managing and matching mechanical system usage to human presence patterns. The drastic improvement in sensing technologies in the last decade have made them a clear candidate in regulating the consumption of energy in the future. A comprehensive evaluation of the current state and gradual progression of occupancy schedules through time is key towards understanding the diverse components of occupancy patterns and structuring any future interventions.

LITERATURE REVIEW

Occupants in Buildings

Understanding and reproducing the complex impact of occupant behavior in buildings can be a challenging task. Occupants can affect the building through primarily two main behavioral categories. People influence the building either passively by their presence, or actively through their interaction with building systems to control their environment and ensure their comfort (Hong et al. 2017). In BPS, occupancy schedules are used to give us a better understanding of the passive presence of individuals in buildings. They feed more importantly into models that depict how individuals are expected to respond to changing environmental circumstances and may include interaction with windows (Fritsch et al. 1990), air-condition systems (Tanimoto, Hagishima, and Sagara 2005) and lighting (Reinhart 2004). Developing the behavioral patterns required to determine and regulate the energy consumption of a building is therefore highly dependent on the fidelity of the occupancy schedules (Yao and Steemers 2005). While the passive impact of occupants can be calculated, the issue lies in the input that feeds these calculations. First there is an unfeasibility in the enquiring of the necessary observational data that is required to generate

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an empirically grounded presence model. Furthermore, the data that is available usually fails to describe the wide range of occupant diversity and is not accurate in terms of temporal representation (Mahdavi and Tahmasebi 2019). Any occupancy schedule therefore relies primarily on various means of data interpolation.

Deterministic Occupancy Schedule

While different approaches are currently used to represent occupant behavior in BPS (Crawley et al. 2008), one of the oldest and most widely adopted are deterministic schedules. Logical assumptions are made to create different patterns based on time of the week and type of building. The simplicity of these initial schedules do not capture the complexity and diversity of human behavior in buildings or take advantage of the computational potential that modern technology provides. The deterministic values of these schedules are mostly derived from codes, standards or the intuition of experienced energy modelers (D'Oca and Hong 2015). The most referenced standard is the ASHRAE 90.1 published in 1989 that has remained relatively unchanged in the 2011 edition (American Society of Heating Refrigerating Air-Conditioning Engineers 2011). The oversimplified nature of these schedules leads to homogenous simulation results (Cowie et al. 2017) that neither capture the stochastic patterns of occupant behavior in buildings (*Annex 66 Final Report* 2018) nor are supported by empirical data. An office building investigated by Sun & Hong displayed a significant 50% deviation from the standard schedules provided by the Department of Energy (DOE) when comparing them to actual observed occupancy presence (Sun and Hong 2017). The deviation of these occupancy schedules from real life behavior patterns allude to the large quantities of energy lost due to mismanagement of mechanical systems. Occupancy schedules that depict human presence across different climate zones have also been standardized and are deterministic, while real life observations have indicated differences due to behavioral parameters (Azar and Menassa 2012).

Probabilistic Models

The failure of deterministic occupancy schedules in capturing the large spectrum of human behavior led to the development of probabilistic generated occupancy schedules. Richardson et al. were one of the first to generate stochastically driven occupancy schedules that attempted to replicate human behavior. The schedules were derived from a large scale Time Use Data (TUD) survey in the UK that analyzed and divided residential behavioral patterns based on household size and day of the week (Richardson, Thomson, and Infield 2008). First Order time inhomogeneous Markov Chains were used in that analysis to generate a model in which the probability of presence at a time step is only dependent on the state of presence at the previous time step (Feller and Teichmann 1967). The resulting model provided single day occupancy schedules that accounted for differences between weekdays and weekends and the number of individuals present (Richardson, Thomson, and Infield 2008). Being driven by probability, the model generates a different schedule every time it runs, producing results more akin to human behavioral patterns. Adopting that approach however creates issues that relate to scarcity of data (Feng, Yan, and Hong 2015), since large amounts of detailed data about households are required (Paatero and Lund 2006) for that analysis. Unlike commercial buildings, collected residential data used for any model, are not based on sensor feedback and simulation experiments, but rather on surveys which have been shown to be inaccurate. (Gauthier and Shipworth 2015). Data mining approaches similar to the one proposed for office buildings (D'Oca and Hong 2015) should be considered in the future, while ensuring that the privacy of inhabitants is not compromised. Page et al. believed calculating occupancy schedules based on a single day like Richardson et al is not inclusive, and attempted to reproduce an entire year in their simulations. They incorporated interruptions in the model in addition to inhomogeneous Markov Chains to account for abnormal events that result in long absences like vacations or sickness (Page et al. 2008). The schedules developed by Richardson et al and Page et al were both critiqued, however, on their shortcomings in being calibrated according to individual characteristics of inhabitants. This is important, since diversity has been shown to influence a deviation of 46% than the recommended ASHRAE standard in office buildings (Duarte et al 2013). Research also indicated that a variation of 150% in energy consumption can be expected depending on the values used to represent occupant behavior (Clevenger and Haymaker 2006). Realizing the importance of occupant behavior in household energy consumption (Guerra Santin, Itard, and Visscher 2009), Wilke et al later built on Richardson et al's research by providing schedules that described the time, type and duration of different activities performed in a day (Wilke, Haldi, and Robinson 2011) (Wilke et al. 2013). While several methods have started to build on the impact of active actions, we believe that research regarding occupant schedules still remains inconclusive. Other papers have also described the integration of stochastic occupancy schedules as scattered and isolated (Cowie et al. 2017).

Occupancy Schedules Moving Forward

While stochastically generated occupancy schedules are better suited for annual evaluation of energy consumption, they fail to represent short term occupant behavior. Mahdavi and Tahmasebi argued that predicted behavior by probabilistic models and their monitored daily counterpart are usually not compared on a one to

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one basis (Mahdavi and Tahmasebi 2015). In the case of Page et al's stochastically generated absence periods (Page et al. 2008), the frequency of days is accurately depicted, but the periods are randomly scattered across the year and do not match the actual absences. Stochastically generated occupancy schedules fail to accurately govern energy regulation on a day to day basis. A study conducted on a high rise commercial building recommended the use of probabilistic occupancy schedules for annual investigations and day-repeated schedules in particular when trying to assess the model (Carlucci et al. 2016). The role of sensing technologies becomes apparent in enhancing the fidelity of those day to day predictions. Although occupancy schedules and sensing technologies are both means of depicting occupant presence in space, the interplay between those two elements have rarely been studied in spite of the capability of the latter in significantly managing the impact of occupants (Dounis and Caraiscos 2009). The work performed by Mahdavi and Tahmasebi is one of the first to appreciate the value of that connection. Surprisingly, non-probabilistic models that were based on onsite observations performed better in the short term (Mahdavi and Tahmasebi 2015). The reliance on sensing technologies for post occupancy evaluation is also critical, since stochastically generated occupancy schedules entail within them a 5% spatial and 10% temporal uncertainty (Carlucci et al. 2016). A study conducted on 18 design phase energy models in Canada indicated that revising the initial assumptions related to occupancy behavior can reduce the estimation error of energy by an average of 32% (Samuelson, Ghorayshi, and Reinhart 2015). Calibration of simulations also enhanced the accuracy of depicting actual energy use in the case of a high rise commercial building in Shanghai (Pan, Huang, and Wu 2007). In order for calibrations to be a realistic solution however, the currently undeveloped evaluation process of occupancy schedules needs to be tackled (Yan et al. 2015). Research must be conducted on a large scale to compare the simulations of occupant behavior against their actual real world counterparts. The probability that an occupant is present, entailed in occupancy schedules, can provide a second evaluating metric that improves the performance of sensing systems. Most visual human detection mechanisms use confidence indices to indicate the certainty that a tracked object is human (Benezeth et al. 2011). When a certain percentage or threshold is met the system recognizes that object as a person. The probability of presence offered by occupancy schedules can therefore act as a supporting mechanism for either increasing or decreasing that percentage threshold. An integration and cross-validation process between sensed information and simulated results can create enhanced energy savings, a topic that has not been thoroughly researched.

Residential Human Sensing Technologies

The importance of sensing technologies is apparent in building types where occupancy schedules are either not obvious or a large uncertainty in the results is evident (Clevenger and Haymaker 2006). Unlike commercial facilities where the functionality of the building dictates a general trend in behavior, occupancy schedules of residential buildings are greatly influenced by the nature of the occupant in terms of their socio-economic status and habits. Occupancy schedules have therefore been proven unreliable in governing day to day energy regulation in buildings (Mahdavi and Tahmasebi 2015). Relying on onsite sensing technologies is important to ensure occupant data is collected and processed correctly. The rapid advancement in sensing accuracy coupled with the steady decrease of integrating such technologies have started to make them a viable solution to the issue of the energy conservation. A clear understanding of the potential and limitations of these technologies must be evaluated before wide-scale implementation can be considered. A focus was therefore placed on developing occupant sensing technologies, and the annex 66 final report provided a framework of multiple sensing mechanisms that can be used separately or collectively. Human sensing technologies can generally be divided into either radio frequency signal technologies or infrared (IR) and video technologies (Yang, Santamouris, and Lee 2016). Infrared occupancy sensors have been used to count the movement of people both exiting in the building and tracking them inside the buildings itself (Gul and Patidar 2015). Passive IR sensors have also been used frequently to measure occupancy in different spaces. Video imaging is currently an emerging field that enables us to accurately track individuals in space, which is important since the presence of multiple occupants has been shown as a behavior impacting trigger (Haldi and Robinson 2010). The large amounts of data, that are a characteristic problem of video image-based sensors, have also been constantly tackled by the progression of compressed sensing (Jung and Ye 2010). In the case of Computer Vision (CV), high accuracy has been shown but with the downside of requiring extensive computational effort (Lam et al. 2009). The fusion of multi-layered data gathering techniques has successfully increased the viability of detecting behaviors and drastically improved energy consumption in high performance buildings (Dodier et al. 2006; Dong et al. 2010). Although the accuracy of sensing technologies is improving, they are still susceptible to error caused by inactivity, airflow and sunshine triggering a sensor. Even with the best accuracy rates for human detection through video image sensors, an error of 3% is usually expected (Benezeth et al. 2011). One of the underlying problems with current sensing systems is their limited application to commercial and

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public facilities. To encourage the widespread application of sensing technologies in the residential sector, a low-cost system should be established. Additional considerations, however, would also have to be made to ensure the privacy of individuals in their own homes is not compromised. The authors are part of a team that is developing a low resolution camera that aims to only capture pixelated frames and helps preserve individual privacy. The low-cost target coupled with the low resolution required for residential application means that higher levels of inaccuracies and mistakes are expected of these sensors. In order to evaluate the viability of that widespread application, a better understanding of the impact of these mistakes is required.

False Positive Measures

An incident where the detection sensor falsely indicates human presence is generally referred to as false positive sensing. False positive sensing can result from a wide variety of factors like the failure of the system to distinguish between pets and humans (Benezeth et al. 2011). The link between sensing technologies and building performance elements mean that these errors result in the activation of household systems like Heating, Ventilation and Air Conditioning (HVAC), consequently leading to energy inefficiency. While many studies have attempted to capture the impact of stochastic occupancy schedule implementation on energy consumption and its components like lighting (Zhou et al. 2015), electrical appliances (Yilmaz, Firth, and Allinson 2017) and BPS (Gunay et al. 2014), a lack of research regarding the impact of false positive errors on building energy consumption is identifiable. The potential value brought by sensing technologies in terms of energy savings would have to be weighed against the cost of the equipment and the scale of their application. The relationship and impact of false positive errors on energy consumption can be acquired through a sensitivity analysis. While a sensitivity analysis has rarely been undertaken to evaluate the impact of false human sensing, it has been applied to various other building elements relating to occupants. Blight and Coley conducted a sensitivity analysis to evaluate the impact of occupancy behaviors on total energy consumption while observing lighting and appliance use (Blight and Coley 2013). The same classical format and methodology used by conventional references (*Sensitivity analysis* 2000) and other reviewed studies (Blight and Coley 2013) can therefore be extrapolated to evaluate false occupant sensing. The impact of a false positive reading of human presence can only be calculated however with developed understanding of how human sensing systems work. Differences can be found between sensing systems (*Annex 66 Final Report* 2018) based on their software configuration and limitations, so a process for breaking down system configuration and rules and extrapolating their effect is important. The workflow of the sensing technology needs to be carefully examined for key elements like Motion Sensor Timeout (MST) intervals that form the base of simulation inputs. These inputs dictate the response of the sensing system to any detection of presence whether true or false. Their implications would influence both the probability of a false positive occurring and the speed at which a false positive reading of human presence can be amended. A general benchmark marking total percentage of energy saved using a regulation system must be set. Responses of simulated energy performance in modeling software like EnergyPlus are then studied with respect to the variations (Ioannou and Itard 2015). In these software simulations all inputs are kept constant, while changes are being tested for the chosen element. Sensitivity analysis in relation to occupancy behaviors is usually performed with Monte Carlo analysis (Lomas and Eppel 1992) (Ioannou and Itard 2015). Regression techniques are then used to understand the relationship between any number of factors in the form of an equation (Blight and Coley 2013). These statistical tools are better equipped in analyzing results where occupant diversity and behavior are present. The sensitivity analysis would finally be applied to measure the maximum allowable rate of errors that still maintain an established benchmark. To conclude, the increasing accuracy of sensing systems due to technological advancements makes its future widespread use in managing energy consumption highly likely but the questions then are: 1) How do false positive readings impact the total amount of energy conserved? 2) Will sensing technologies be capable in removing the reliance on preset occupancy schedules in the future? 3) How do sensing technologies currently compare to the latest generated occupancy schedules? In this paper we will focus on quantitatively evaluating the impact of false positives on energy consumption. The acquisition of observational data that establish error frequencies in regard to specific sensing systems is left for future research.

EXPERIMENT DESIGN

Research Goals and Objectives

This paper aims to enhance our understanding of the relationship between occupancy schedules and sensing technologies, and answer the following four questions:

1) How do sensing technologies currently compare to stochastic occupancy schedules?

2) How sensitive is a building's energy consumption to a false positive reading?

3) What is the maximum allowable false positive reading that outperforms a 30% energy loss benchmark?

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4) Are low cost sensing technologies capable of removing the reliance on preset occupancy schedules in buildings?

The answer to these questions should help us evaluate the accuracy and uncertainty in probabilistic occupancy models. It can also help decision makers evaluate the viability of relying on sensing technologies as the sole means of regulating energy consumption in future buildings.

Experiment Logic

The experiment aims at understanding the impact of a false positive reading on total energy consumption. A false positive reading is an occurrence where a building sensing system falsely indicates the presence of a human and activates the HVAC systems accordingly. This experiment aims to represent the occurrence of a false positive in stochastically generated occupancy schedules. Figures 1 and 2 illustrate the changes made to simulate a false positive. First an initial schedule is used as a substitute for real on-site observational data and is assumed to be a true sample of behavioral patterns in a space. The original dataset consisting of 0 and 1, that respond to the absence or presence of individuals at a particular time period, respectively, is then altered. Since sensing technologies should recreate the initial occupancy schedule, the deviation or change is accordingly analogous to a false positive reading registered by the system. This framework is adopted for the experiment and initial occupancy schedules are therefore modified to represent the presence of a false positive reading. The change in an initial occupancy schedule due to a false positive and accordingly the amount of time the HVAC system is running in the absence of people is a function of the scanning frequency. The scanning frequency is the interval or time that a machine takes in making routine consecutive scans of the environment after human presence has been

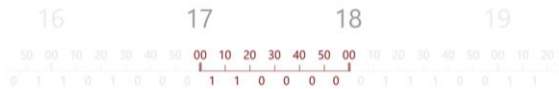

Figure 1: Initial Occupancy Schedule

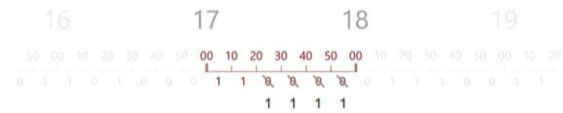

Figure 2: Modified Occupancy Schedule

detected. The scan proceeding a false positive, is where the system can rectify the error and shut down the operated building systems. Scanning frequency is therefore used as a measure of the time duration of a false positive and assists in quantifying how the occupancy schedules will be modified. The difference between the total HVAC thermal load of the initial occupancy schedule and the modified one is the impact of a false positive reading.

Research Design

Figure 3 showcases the experimental workflow:

1) Using a TUD set to develop a large occupancy behavior database.
2) The dataset is analyzed and a probabilistic model that generates occupancy schedules is employed.
3) Energy simulation for both the initial and modified occupancy schedule are conducted.
4) The results are compared to estimate the impact of a false positive reading in terms of total energy consumption.

This study employed the model produced by Richardson et al (2008) for residential buildings in the UK as a base for generating the occupancy schedule. A sample of four occupancy behaviors patterns from the model have been used as the base. A false positive reading is considered a randomly occurring phenomenon, meaning that there is

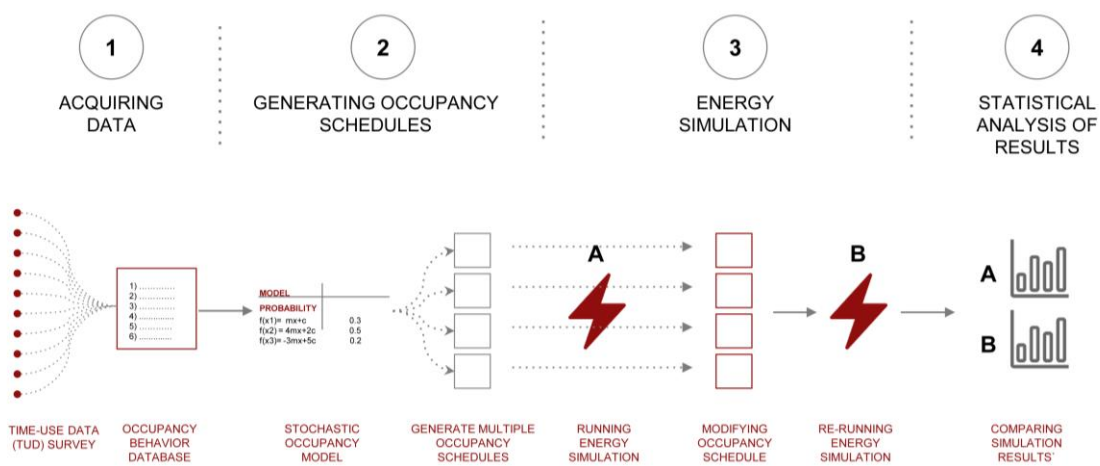

Figure 3: Experiment Workflow

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no pattern to when they occur in the day. They are restricted, however, to occur at times in which the occupancy schedules indicate lack of human presence. The impact of false positive readings was tested for varying number of occurrences and different scanning frequencies of sensing systems. The performance evaluation and accuracy of a specific sensing technology is also not the objective of the experiment. The study only uses the limitations in the workflow of a sensing technology such as sensing frequency to create a measure of the impact of false positive sensing.

Simulation Model

The residential setting depicted in figure 4 was modeled in the Grasshopper interface for Rhino3D CAD

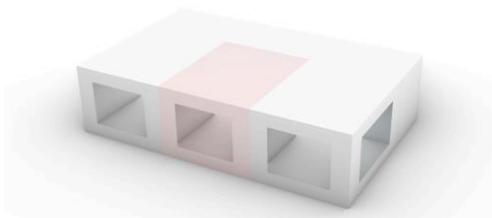

Figure 4: 3D CAD Model for the Experiment

software, then simulated through EnergyPlus using Ladybug Tools. The area of the modeled room is 20 m^2 (5m(L) x4m(W)) with a height of 3m and a southern facing façade window located at the narrow end with a 40% window-to-wall ratio. The exterior walls and roofs have an R-Value of 1.94 m2-K/W and 3.53 m2-K/W respectively. All interior surfaces were considered adiabatic. The HVAC system used for the residence is the Packaged Terminal Air Conditioner Heat Pump (PTHP). The number of occupants is one. Equipment, lighting and HVAC schedules were then matched to the stochastically generated occupancy schedules. The simulations were performed with the Typical Meteorological Year (TMY2) weather file for Atlanta, Georgia, USA for the period from June 21-June 27. The targeted temperature range in the simulated model was 22-25 °C. The output being monitored is specifically cooling loads in that period.

RESULTS

First, the total variation between the initially chosen schedule and a sample of its counterparts was analyzed. The variation, as seen in Table 1, was on average evenly distributed between the number of hypothetical false positive occurrences, where a 1 was registered instead of a 0 and its opposite, a false negative. The total amount of variation was relatively high at 34.8% clearly identifying the incapability of probabilistic occupancy schedules in governing day to day energy regulation.

Table 1: Probabilistic Occupancy Schedule Variation

Total Variation(%)	False Positive(%)	False Negative (%)
34.8	18	16.8

The next experiment, demonstrated in figure 5, compared the average impact of a single false positive for different scanning frequencies. A total of twenty false positives were added to the weekly occupancy schedules. The results of the experiment reveal that shorter time intervals between consecutive scans produced on average smaller percentages of energy being lost per false positive. A 60 min scanning frequency accounted for a 1.49% of energy being lost per false positive, while a 10 min scanning frequency resulted in an average 0.51% weekly energy loss per false positive. These

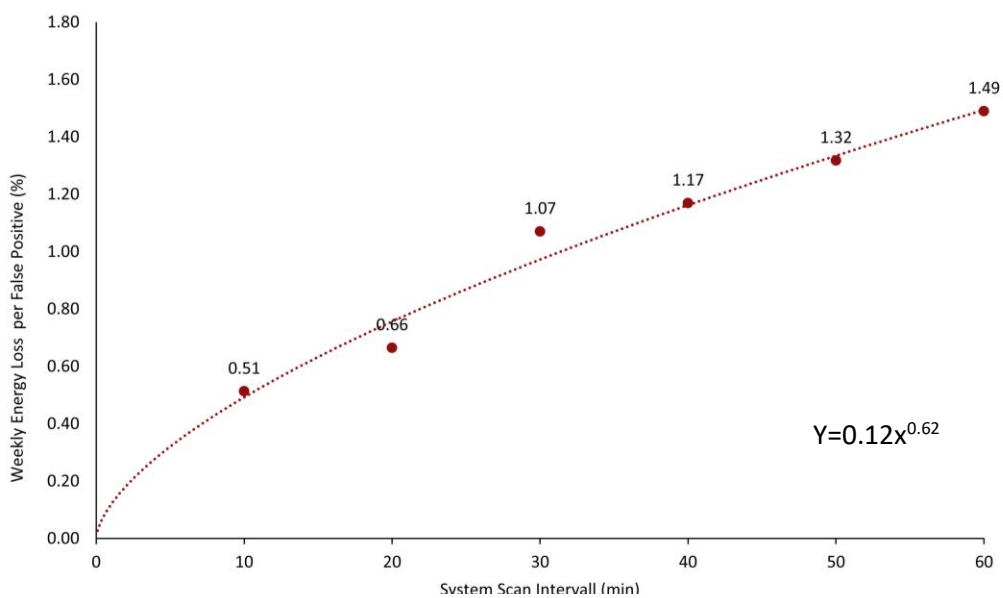

Figure 5: Scanning Frequency's Effect on False Positive Impact

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percentages can result in significant amounts of energy being lost, as six false positives in the case of the 60 min interval scan can result in an approximate 9% loss of weekly energy. The relationship between the weekly percentage of energy lost and the time interval of the scanning system can be best described by a power function indicated in the graph. Higher time periods of scanning frequencies have larger percentages of energy loss but does not follow the same ratio as that of the time factor. The amount of additional lost percentage of energy per added minute between scans falls off with higher time periods.

The standard deviation from the average percentage of energy lost, per false positive within the different scanning frequencies, as shown in Table 2, was significant. Occurrences of false positives resulted in small quantities of energy being lost in some cases and large quantities in others. Finally, the weekly number of false positives and consequently required time that resulted in 30% energy being lost was shown in figure 6 to be high. In the case of the 60 min interval, a weekly 22 hours were required to result in the 30% energy loss benchmark.

Table 2: Standard Deviation for False Positive Impact

Scanning interval (min)	60	50	40	30	20	10
Weekly energy lost per false positive (%)	1.49	1.32	1.17	1.07	0.66	0.51
Standard Deviation(%)	0.74	0.8	0.7	0.77	0.49	0.53

DISCUSSION

The results of this experiment had findings from which properties of false positive readings can be inferred. The first finding indicated that the additional energy percentage loss per false positive is not proportional to the time of the scanning frequency. This can be attributed to the fact that in larger false positive intervals the amount of energy required to maintain a desired temperature in the intermediate periods, within the false positive, is lower than the effort required to regulate the environment after first starting the system. The large deviation on the other hand indicated that the time at which the random occurring false positive manifested played a significant role in the amount of energy being lost. That large deviation can be attributed to multiple factors. First, we need to consider the environmental climate at the time at which a false positive occurs. Outdoor environmental conditions at peak noon in a hot climate would require more energy to regulate a space to the desired temperature than that of an 8 PM afternoon. The occupancy pattern prior to the occurrence of a false positive would also play an important role. The occurrence of a false positive in a space that has been uninhabited for a long period of time would also require larger amounts of energy to bring the indoor temperature to the comfort level rather than a false positive occurring immediately upon the departure of inhabitants. Finally, the equivalent false positive time required for the 30%

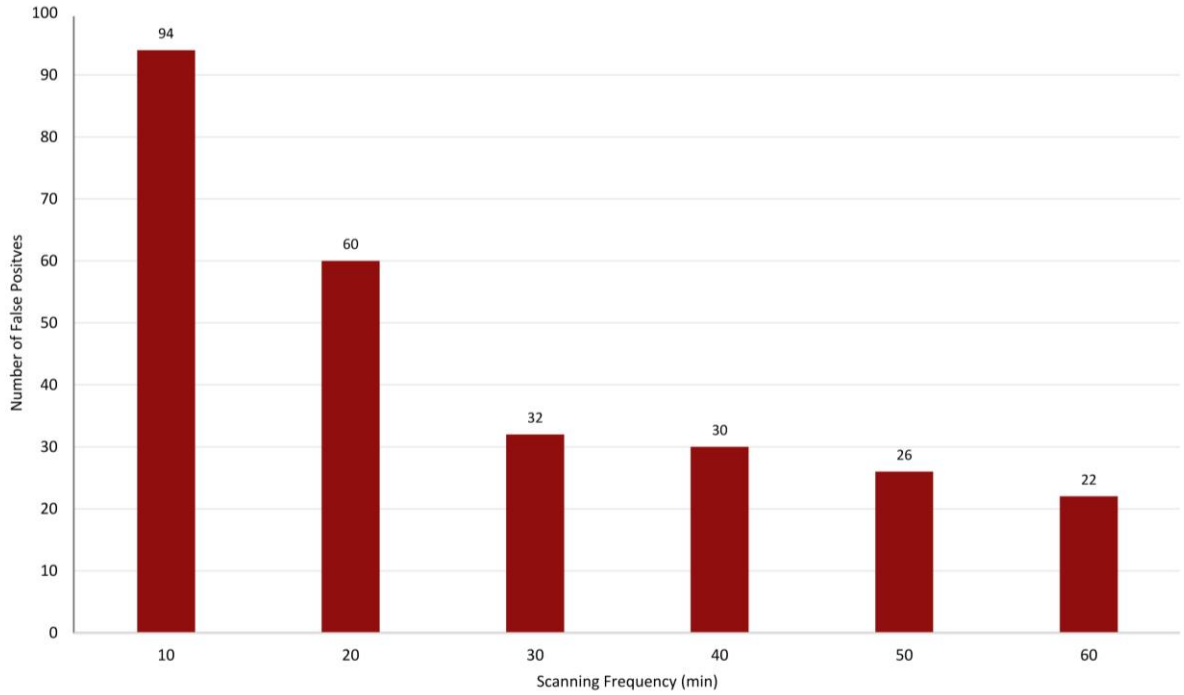

Figure 6: Number of false positives that result in a 30% Energy Loss

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loss benchmark is high. While false positives pose a great threat to the amounts of energy being conserved in the context of a 30% energy loss benchmark, sensing systems warrant their use.

The initial results were capable, however, of capturing the impact of occurrences only at a particular point in time. Future expansions on this research should conduct full year evaluations and seasonal explorations in order to holistically convey the effect of false positive readings and give us better gauges of its temporal relationships. The impact of false positives in different temperatures should be evaluated not only in the context of the amount of energy lost but must also be tied to the possible compromised occupant comfort by the occurrence of an error. The scanning frequency can play a role on whether a system shutdown due to a sensing error is perceived by the occupant in a space. The extent and speed by which the comfort inside a room deteriorates is then a function of building characteristics and the environmental context. It is important that a compromise is found that sustains relatively good comfort levels in the event of an error to ensure continual usage of a system.

The experiment was also conducted in a particular geographical location, namely Atlanta, Georgia. In future research the same occupancy schedule with the same frequencies of false positives should be evaluated in different climate zones to test their effect on the percentage amount of energy lost. Future research should also investigate larger settings with multiple occupants as a more representative proxy for most residential apartments. The results of this experiment clearly elude to the notion that smaller periods between consecutive scans provide lower energy loss figures. The lowest sensing frequencies, however, might not necessarily provide the holistically best results in terms of total energy consumption. An extension to the initial research should account for the amount of energy being used by the sensing system to conduct a full scan of environment. A tradeoff relationship should be established that weighs the benefits of short scanning frequency periods against the amount of energy consumed for the consequently higher number of scans performed by the system. This can help guide designers in adjusting the parameters of these sensing systems to provide the most efficient results in terms of overall energy consumption.

Finally, while some results of this experiment are self-explanatory like the average percentage of energy being lost due to a false positive occurring, others require observational data to give more context to the results and make them better grounded. The number of false positives that can occur should be tested using observational data from a real-world setting. These data can provide a baseline against which results can be compared and help evaluate if the occurrence of 40 false positives in a single week is something to be expected or a low figure when compared to reality. That context can consequently help us understand the threat that false positive pose on the amount of energy being conserved.

CONCLUSION

Human behavior, represented through occupancy schedules in BPS, is considered one of the only elements that inform human energy consumption in buildings. Probabilistic driven occupancy models are our current best tools for replicating the complex behavioral patterns of humans in buildings, but are only accurate for long-term trend identification and fail in informing most short-term governing of energy. Technological advancement on the other hand has led to the partial integration of developing sensing technologies in building programs, but are still lacking in term of widespread use. The mutually beneficial relationship between occupancy schedules and sensing technologies needs to be utilized, where sensing technology can work in the calibration process of occupancy schedules in large scale buildings. Gathered data should constantly shape the ever-changing nature of human behavior and match occupancy schedules that govern building systems to actual human patterns. On the other hand, occupancy schedules can inform and reduce the errors experienced by sensing technologies. The wide-scale implementation of sensing technologies in our daily lives however, require new low cost systems that entail inaccuracies in their use. This research has provided some insights on the impact of human false positive sensing and a comparison of its performance in relation to probabilistically generated occupancy schedules. The high deviation between the different probabilistically generated occupancy schedules and the relatively low percentage of weekly energy lost per false positive warrant the use of sensing technologies. The amount of energy loss per false positive seems to be relatively low which encourages the use of relatively low cost sensing technologies for wide scale implementation at the sacrifice of some accuracy. The claim however remains to be supported by real life observational data of average false positive frequencies for different sensing technologies. The number of false positives required to surpass the 30% benchmark are relatively high. Initial results indicate the benefit of the wide-scale integration of sensing technology in regulating energy consumption in United States residential buildings. In conclusion, low cost sensing technologies seem to be ready to replace preset occupancy schedules in buildings. Further expansion and examination of the impact of false positives, however, can provide together with the social and economic dimensions of sensing technologies, better insights on the feasibility of fully integrating sensing systems in our everyday lives. The BPS community will then be prepared for the inevitable widespread integration of sensing technologies in the future by having a grasp on all of its associated parameters.

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ACKNOWLEDGEMENT

The information, data, or work presented herein was funded in part by the Advanced Research Projects Agency-Energy (ARPA-E), U.S. Department of Energy, under Award Number DE-AR0000940. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

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